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Big Questions, Little Answers: Terrorism Activity, Investor Sentiment and Stock Returns

Konstantinos Drakos[*♣]

Abstract

Motivated by the investor sentiment literature and assuming that terrorist activity influences investor mood the paper explores whether terrorism exerts a significant negative impact on daily stock market returns for a sample of 22 countries. The employed empirical specifications are based on flexible versions of the World CAPM allowing for autoregressive conditional heteroscedasticity. The results suggest that terrorist activity leads to significantly lower returns on the day of terrorist attack occurrence. In addition, the negative effect of terrorist activity is substantially amplified as the level of psychosocial effects increases. On the one hand this evidence sheds light to the underlying mechanism via which terrorism affects stock markets while on the other hand provides further empirical support for the sentiment effect.

JEL Code: C33, E44, G15

Keywords: Sentiment, Terrorism, Stock Market, Panel, Pooled Panel ARCH

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1. Introduction

The relative easiness of buying and selling stocks results in their prices being very sensitive to the revelation of new information. This property generally manifests itself in the occurrence of unforeseen events and especially in the case of adverse shocks such as mega[1]-terrorist incidents. For instance, on September 11th 2001 the day of the Twin Towers terrorist attacks the MSCI World Index lost 1.98 % of its value even though the US stock market did not operate. A second round loss of 2.57 % was recorded on the September 17th when the US market re-opened. Similarly, on March 11th 2004 the day of the Madrid attacks the MSCI fell by 1.72 %. To appreciate the significance of these market reactions perhaps two pieces of information would suffice. First, the average daily change of the MSCI World Index for the period 1994-2004 was 0.027 %. Second, the losses on these three days make it in the top 100 worst trading days in terms of returns during this 11-year period (the September 17th, September 11th and the March 11th losses were the 20th, the 54th and the 94th worst trading days respectively). The unfavorable impact on stock markets caused by mega-terrorist events has also been empirically documented with formal econometric models in the extant literature (Carter and Simkins 2004; Chen and Siems 2004; Drakos 2004; Eldor and Melnick 2004; Gulley and Sultan 2006; Amélie and Darné 2006; Chesney and Reshetar 2007; Nikkinen *et al.*, 2008).

However, the literature has not so far investigated whether the overall terrorist activity exerts any systematic effect on stock markets. A plausible channel via which terrorist activity could exert a negative impact on stock market returns is through investor sentiment. In particular, if terrorist attacks were a mood proxy then their occurrence is expected to deteriorate investor sentiment and consequently put a downward pressure on stock prices.

The paper makes a twofold contribution to the literature. First, in contrast to previous research that has focused on selected major terrorist acts, it tests whether the overall terrorist activity significantly affects stock returns. This is done for a large number of countries and a large time span using an econometric framework that controls for global risk factors. Second, by linking terrorism to investor mood it derives testable hypotheses that relate directly to the investor sentiment literature. In particular, apart from the investigation of the potential negative effect of terrorism on stock returns, it also explores whether this effect is a function of the level of psychosocial impact caused by terrorist incidents.

The remainder of the paper is organized as follows. Section 2 explains the a priori motivations for exploring the link between terrorism and stock returns. Section 3 discusses the econometric methodology and the hypotheses to be tested. Section 4 describes the data used in the subsequent analysis. Section 5 presents and discusses the empirical findings and finally Section 6 concludes.

2. Motivation

There is a burgeoning literature exploring the asset pricing impact of several behavioral biases (for extensive and in depth reviews see Hirshleifer 2001; Shiller 2003; Stracca, 2004). A strand of this literature has documented various exogenous factors that capture mood (and therefore investor sentiment) as being correlated with stock returns. These exogenous factors could be part of what Rick and Lowenstein (2007) describe as incidental emotion influences on risky decision making. As mood indicators previous research has utilized a variety of variables such as sunshine (Saunders 1993; Hirshleifer and Shumway 2003), sleep patterns (Kamstra *et al*, 2000), temperature (Cao and Wei 2005), daylight (Kamstra *et al*, 2003), lunar phases (Yuan *et al*, 2006), and international soccer results (Edmans *et al*, 2007).

The core question is whether one can consider terrorist activity as a mood proxy. Edmans *et al*. (2007) argue that the chosen mood indicator must satisfy three criteria to rationalize its link with stock returns. First, the selected variable must drive mood in a substantial and unambiguous manner, so that its effect is vigorous enough to be reflected in asset prices. Second, the variable must affect the mood of a large proportion of the population so it is likely to influence investors. Third, the effect must be correlated across the majority of individuals within a country.

Terrorist events, that are by default unforeseen exogenous to the stock market shocks, seem the ideal candidate as a proxy for investor mood satisfying all three criteria. In fact it is rather hard to think of other (social) events causing so pronounced and highly correlated mood swings within a country's population. Under the null hypothesis of Market Efficiency terrorist activity should not affect stock returns. The alternative, that terrorist incidents significantly affect stock returns, would be compatible with models of investor sentiment. Moreover if investor sentiment was affected by terrorism one could impose further structure on the potential effects. First, on trading days that terrorist incidents have occurred risk-adjusted returns should be significantly lower. Second, the (absolute) impact on stock returns should be an increasing function of the degree of the event's severity. The negative impact on returns is expected since terrorist activity is assumed to induce a deterioration of sentiment. The dependence of the effect on severity captures the extent that the population is affected and also whether it is correlated across individuals. Clearly as the severity of a terrorist incident increases so does the likelihood that it affects, and in the same direction, a higher proportion of the population.

3. Econometric Methodology and Hypotheses

We proceed by considering terrorist activity $\left(terr_{i,t}\right)$ as a one-sided risk producing potentially adverse effects on the stock market (Abadie and Gardeazabal 2008). We assume that it is a random variable following a Bernoulli process where with probability $\left(p_{i,t}\right)$ a terrorist incident takes place in country (i) and day (t). We define an indicator variable which is constructed from observed terrorist activity across time and countries and corresponds to realizations of this Bernoulli process. Hence the indicator variable is defined as follows:

$$S_{i,t} = \begin{cases} 1, & \text{if a terrorist incident took place in country } i \text{ in time } t \\ 0, & \text{otherwise} \end{cases} \qquad \textbf{(1)}$$

As discussed earlier one expects that certain terrorist incidents of extreme severity and audacity might produce a higher (negative) impact compared to the average terrorist attack. To this end we will distinguish between terrorist incidents that had none or minor or moderate or major psychosocial impacts. Our prior is that terrorist activity's negative effect on stock markets will be exacerbated as the incidents are of higher severity. Thus, conditional on the occurrence of a terrorist incident we define three dichotomous variables capturing the level of psychosocial impact it caused as follows:

$$MAJ_{i,t} = \begin{cases} 1, & \text{if the incident caused a major psychosocial impact} \\ 0, & \text{otherwise} \end{cases} \qquad \textbf{(2)}$$

$$MOD_{i,t} = \begin{cases} 1, & \text{if the incident caused a moderate psychosocial impact} \\ 0, & \text{otherwise} \end{cases} \qquad \textbf{(3)}$$

$$MIN_{i,t} = \begin{cases} 1, & \text{if the incident caused a minor psychosocial impact} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$NON_{i,t} = \begin{cases} 1, & \text{if the incident caused no psychosocial impact} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Now consider a vector of stock market index prices, $\left(I_{i,t}\right)$, where (i) and (t) denote country and day respectively. The daily return $\left(R_{i,t}\right)$ is calculated as follows:

$$\left(R_{i,t}\right) \approx \ln\left(\frac{I_{i,t}}{I_{i,t-1}}\right) \tag{6}$$

We begin by employing a one-factor setting where the relevant source of global risk is a benchmark portfolio proxied by the world equity market portfolio[2]. In this context Grauer *et al*. (1976) and Adler and Dumas (1983) have shown that the global value-weighted market portfolio is the relevant risk factor. Assuming that investors do not hedge against exchange rate risks and a risk-free asset exists the conditional version of the world CAPM implies the following behavior for excess returns:

$$\left[E\left(R_{i,t}\right) - R_{WRF,t}\right] = c_1\left[E\left(R_{WMP,t}\right) - R_{WRF,t}\right] + u_{i,t} \tag{7}$$

where E stands for the expectations operator, $\left(R_{WMP,t}\right)$ is the daily return on the World Market Portfolio $\left(WMP_t\right)$, $\left(R_{WRF,t}\right)$ denotes the world risk-free rate, $u_{i,t}$ is a random disturbance term and c is a constant estimable parameter.

The actual empirical specification we use is rather more flexible allowing, not only for contemporaneous sensitivity, but also for a dynamic relationship between $\left(R_{i,t}\right)$ and $\left(R_{WMP,t}\right)$ where lagged values (of order J) of the latter will be included as regressors in the model. Additionally, we allow $\left(R_{i,t}\right)$ to exhibit an autoregressive component of order (N). We further augment the model with fixed time-effects denoted by $(year)$ to capture aggregate conditions that may change from year to year. Furthermore, the empirical finance literature has established that the return generation process is not uniform across months in a given year and/or across days in a given week. These two effects that typically are considered as calendar anomalies are known as month and day of the week effects (French 1980; Gibbons and Hess 1981; Jaffe and Westerfield 1985; Kato and Shallheim 1985; Board and Sutcliffe 1988; Choudhry 2001). To take these potential effects into account we construct two sets of dummies. A set of five dummies $\left(day_{d.i,t}\right)$ whose typical element attains the value of unity on a given day of the week and zero otherwise. Similarly $\left(month_{m,i,t}\right)$ stands for a set of twelve dummies whose typical element attains the value of unity on a given month of the year and zero otherwise.

Thus the model specification is:

$$\begin{aligned}\left(R_{i,t}\right) = \alpha_0 + \alpha_1\left(S_{i,t}\right) + \left(\sum_{j=0}^{J} c_j R_{WMP,t-j}\right) + \left(\sum_{n=1}^{N} \phi_n R_{i,t-n}\right) + \sum_{k=1}^{K} \gamma_k\left(year_{k,i,t}\right) + \sum_{m=1}^{11} \delta_m\left(month_{m,i,t}\right) \\ + \sum_{d=1}^{4} \lambda_d\left(day_{d,i,t}\right) + \mu_i + \varepsilon_{i,t}\end{aligned} \quad \textbf{(8)}$$

Given the panel dimension we condition on country heterogeneity allowing for an unobserved effect μ_i treated as random, assuming that $E\left(R_{i,t-j}\mu_i\right) = 0 \quad \forall\ i, j, t$.

The parameter of interest is (α_1) whose significance and sign will shed light on the issue whether terrorist activity affects stock returns. Our prior is that (α_1) is negative:

$$\left(\frac{\partial R}{\partial S}\right) = \alpha_1 < 0$$

In order to test the potential dependence of investor sentiment on the severity of terrorist incidents we break down the set of terrorist events into three mutually exclusive parts each one identifying a given level of severity using the four dummies defined in (2)-(5). The model then becomes:

$$\left(R_{i,t}\right)=\alpha_0+\alpha_1^*\left(NON_{i,t}\right)+\alpha_2^*\left(MIN_{i,t}\right)+\alpha_3^*\left(MOD_{i,t}\right)+\alpha_4^*\left(MAJ_{i,t}\right)+\left(\sum_{j=0}^{J}\beta_j R_{WMP,t-j}\right)+\left(\sum_{n=1}^{N}\phi_n R_{i,t-n}\right)+$$

$$+\sum_{k=1}^{K}\gamma_k\left(year_{k,i,t}\right)+\sum_{m=1}^{11}\delta_m\left(month_{m,i,t}\right)+\sum_{d=1}^{4}\lambda_d\left(day_{d,i,t}\right)+\mu_i+\varepsilon_{i,t} \tag{9}$$

Moreover, given that the psychosocial dummies attain the value of unity if and only if a terrorist incident has taken place model (9) is equivalent to model (8). In other words, if the variation of terrorist activity explained part of the variation in daily returns, i.e. if $\left(\alpha_1\right)$ (from equation 8) turns out to be significant, so will $\left(\alpha_1^*+\alpha_2^*+\alpha_3^*+\alpha_4^*\right)$ and they will also carry the same sign. Hence we expect to reject the hypothesis $H_0:\left(\alpha_1^*+\alpha_2^*+\alpha_3^*+\alpha_4^*\right)=0$ in favor of the alternative $H_1:\left(\alpha_1^*+\alpha_2^*+\alpha_3^*+\alpha_4^*\right)<0$.

Additionally if the level of psychosocial impact drives investor sentiment we also expect to reject the joint hypotheses $H_0:\alpha_1^*=\alpha_2^*=\alpha_3^*=\alpha_4^*=0$ in favor of the alternative that at least one parameter is significantly negative. Finally we also expect that $\left|\alpha_1^*\right|<\left|\alpha_2^*\right|<\left|\alpha_3^*\right|<\left|\alpha_4^*\right|$ implying that the negative effect on returns increases monotonically with the level of deterioration in investor sentiment as proxied by the psychosocial impact of terrorist attacks.

A well established empirical regularity is the volatility clustering exhibited by daily returns (Engle 1982; Bollerslev 1986). Thus, in order to control for this we employ a Pooled Panel GARCH (PP-GARCH hereafter) model for the conditional volatility of stock returns (Cermeno and Grier 2006). Although multivariate GARCH models are also available they are not practical for most panel applications because they require the estimation of a large number of parameters which consumes degrees of freedom rapidly. In contrast, PP-GARCH estimation by imposing common dynamics on the variance-covariance process across cross-sectional units reduces the number of parameters dramatically ensuring parsimony. Furthermore, the PP-GARCH model does not imply constant cross-sectional correlation over time. We then allow a more flexible specification for the error term with:

$E\left(\varepsilon_{i,t}\right)=0$ and $E\left(\varepsilon_{i,t}^{2}\right)=\sigma_{i,t}^{2}$

In particular, assuming that $\varepsilon_{i,t} \sim N\left[0,\Omega_{i,t}\right]$, *i.e.* are multivariate normal error terms with a time-varying conditional variance-covariance matrix produces a PP-GARCH model (Cermeno and Grier 2006). The variance-covariance matrix $\Omega_{i,t}$ is time-dependent and its diagonal and off-diagonal elements are given by the following equations:

$$\sigma_{i,t}^{2}=\phi_{0}+\sum_{n=1}^{N}\phi_{n}^{*}\sigma_{i,t-n}^{2}+\sum_{l=1}^{L}\eta_{l}v_{i,t-l}^{2}$$

$$\sigma_{i,j,t}=\psi_{0}+\sum_{n=1}^{p}\psi_{n}\sigma_{i,j,t-n}+\sum_{m=1}^{k}\rho_{m}v_{i,t-m}v_{j,t-m},\ \text{ for } i\neq j \tag{10}$$

where the ϕ^{*}'s, ψ's, η's and ρ's denote unknown constant parameters to be estimated.

4. Data Sources and Variables Description

4.1 Terrorist Activity

The most recent and complete terrorism database is the **Global Terrorism Database** (*GTD*) developed at the University of Maryland, containing both domestic and international incidents. The database consists of two parts (*GTD1*)[3] that records worldwide events for the period 1970 to 1997[4] and (*GTD2*)[5] for the period 1998 to 2004. We collect information regarding the exact calendar date (year, month, day) and the location (country) of terrorist incidents.

Table 1 reports the top 40 countries in terms of the count of terrorist incidents they witnessed during the period under consideration[6]. Between them they account for about 86 % of total worldwide terrorist activity in the period 1994-2004. Colombia (9.20 %), India (7.17 %), Algeria (7.08 %), and Pakistan (6.75 %) are the countries with the highest shares of terrorist activity. The countries with the lowest shares are Brazil (0.60 %), Venezuela (0.56 %), Angola (0.53 %) and Yemen (0.50 %).

----------***Table 1***----------

The *GTD* also provides information regarding the psychosocial impacts of terrorist attacks classifying them as having none, minor, moderate, or major impact. However this information has been recorded only for the post 1998 period. According to the GTD manual:

> **"Where the source materials contain relevant information, the extent of the psychological /social damage brought about by the incident is estimated. This applies to short-term consequences of the incident (days to weeks) rather than long-term societal changes. This variable includes the following values: Major (Far-reaching – national or international – effects; tangible changes in behavior of the majority of the affected public, including symptoms of Post-traumatic Stress Disorder, or Acute Stress Disorder), Moderate (General anxiety and unease, but significant psychosocial effects and/or behavioral changes among a subset or minority of the exposed public), Minor (Some anxiety or unease, without any significant behavioral changes), None".**

Figures 1 and 2 depict the distribution of attacks with major and moderate psychosocial impacts across years and countries respectively. The countries with the highest number of incidents with major psychosocial impact are the USA (8), Russia (5), and Israel (3).

----------***Figure 1***----------

----------***Figure 2***----------

4.2 Stock Markets

Daily closing prices from 3/1/1994 to 30/12/2004 in local currencies for broad stock market indices where obtained from **Datastream.** Due to data unavailability for various countries we are left with 22 indices namely: Bovespa (Brazil), IGBC INDEX (Colombia), Hermes (Egypt), CAC 40 (France), DAX 30 (Germany), Athex Composite (Greece), BSE (India), Jakarta SE Composite (Indonesia), Israel TA 100 (Israel), Blom (Lebanon), IPC BOLSA (Mexico), Karachi SE 100 (Pakistan), Lima SE General IGBL (Peru), SE-IPSEi (Philippines), RTS INDEX (Russia), Madrid SE General (Spain), Colombo SE All Share (Sri Lanka), Bangkok SET (Thailand), ISE NATIONAL 100 (Turkey), FTSE All Share (UK), NYSE Composite (USA), Venezuela SE General (Venezuela). Table 2 provides the main descriptive statistics for countries' daily returns.

----------***Table 2***----------

Returns across all countries share the common characteristic of significant deviations from normality, which is a usual property of daily returns. In particular for each country the return series is leptokurtic indicative of 'fat tails'. For Germany, India, Israel, Pakistan, Russia, Spain, UK and USA skewness attains negative values indicating that their returns' distributions are left-skewed while for the remaining countries skewness is positive and therefore return distributions are right-skewed.

Our basic empirical specification assumes a single risk factor corresponding to the global equity market portfolio, which we proxy by the World Morgan Stanley Capital International (MSCI World) equity market index. In a later section we conduct sensitivity analysis by assuming a three-factor model where we augment the one factor model with:

- $\left(SMB_{WM,t}\right)$ defined as the difference between the return on a portfolio of small capitalization stocks and the return on a portfolio of large capitalization stocks (SMB, small minus big), and
- $\left(HML_{WM,t}\right)$ defined as the difference between the return on a portfolio of high book-to-market stocks (value) and the return on low book-to-market (growth) stocks (HML, high minus low), which proxies the value or distress premium.

Data construction was based on the World Morgan Stanley Capital International, **Small**, **Large, Value** and **Growth** indices. Descriptive statistics for the three factors' daily returns (and their constituents) are given in Table 3. Similar to the national market returns the sample properties of the benchmarks portfolios show substantial deviations from normality, while all of them are leptokurtic.

----------***Table 3***----------

Table 4 shows the total number of terrorist attacks as well as the number of trading days on which they occurred for the list of countries comprising the sample to be analyzed.

----------***Table 4***----------

The countries in the sample account for just above 71 % of worldwide terrorist incidents (10282 / 14402). The number of trading days in which terrorist attacks occurred differs from the number of attacks simply because there are several instances that multiple attacks took place in a given day. The ratio of the number of trading days that attacks occurred over the total number of trading days provides a rough estimate of the unconditional probability of terrorist attack occurrence. The average unconditional probability that at least one terrorist attack will occur in a given trading day across the 22 countries is about 7.5 % with an unconditional standard deviation of about 4.5 %. This shows that terrorist activity is a relatively frequent phenomenon for these countries. In fact for India the probability is above 21 %, for Pakistan is almost 14 %, for Russia 11.5%, for Colombia, Turkey, UK is 11%, while for Philippines and Sri Lanka is just above 10 %. Thailand, Venezuela and Brazil are associated with the lowest probabilities of terrorist occurrence with 2.67 %, 2.42 %, and 2.32 % respectively.

5. Terrorism and Stock Returns: Empirical Results

Table 5 reports the estimation results from three alternative specifications based on the one-factor world CAPM estimated by Random-Effects, and two pooled regressions allowing for ARCH(1) and ARCH(2) processes. Note also that we set all dynamics to five lags. According to the results ARCH effects are significant verifying the sample properties discussed earlier and furthermore based on a Likelihood Ratio test the PP-ARCH(2) outperforms the PP-ARCH(1). Thus, the quantification of terrorism's effects on stock returns is based on the PP-ARCH(2) specification.

National returns are significantly affected by the world market portfolio return whose impact declines monotonically with the lag order. In addition, national returns exhibit a significant autoregressive component where the first and fourth lag enter the models positively while the second, third and fifth negatively. As it regards to the coefficient of terrorist activity it attains significantly negative signs in all three specifications. The point estimate of the terrorist occurrence variable suggests that the average reduction in stock returns is about -0.049 %.These findings suggest that national returns are significantly lower on days of terrorist attack occurrences and therefore provide prima facie evidence in favor of the sentiment mechanism.

----------***Table 5***----------

5.1 Sensitivity analysis: Three-Factor Model and Financial Crises

In this section we investigate the robustness of our previously reported findings by employing alternative model specifications. First, we extend the return generating process by considering that international returns are driven by a world version of the three-factor model (Fama and French 1993, 1996). The conditional version of the three-factor model is as follows:

$$\left[E\left(R_{i,t}\right)-R_{WRF,t}\right]=\beta\left[E\left(R_{WMP,t}\right)-R_{WRF,t}\right]+\theta\left(HML_{WM,t}\right)+\omega\left(SMB_{WM,t}\right)+u_{i,t} \tag{11}$$

The employed empirical model is of the following form:

$$\begin{aligned}\left(R_{i,t}\right)=\alpha_0+\alpha_1\left(S_{i,t}\right)+\left(\sum_{j=0}^{5}\beta_j R_{WMP,t-j}\right)+\left(\sum_{j=0}^{5}\theta_j R_{SMB,t-j}\right)+\left(\sum_{j=0}^{5}\omega_j R_{HML,t-j}\right)+\\ +\left(\sum_{n=1}^{5}\phi_n R_{i,t-n}\right)+\sum_{k=1}^{10}\gamma_k\left(year_{k,i,t}\right)+\sum_{m=1}^{11}\delta_m\left(month_{m,i,t}\right)+\sum_{d=1}^{4}\lambda_d\left(day_{d,i,t}\right)+\mu_i+\varepsilon_{i,t}\end{aligned} \tag{12}$$

To further explore the robustness of results we control for various financial shocks that had global impacts. In particular we identify four such shocks: the Mexican Peso Crisis, the Asian Crisis, the Russian Crisis and the recent corporate scandals (Enron, Worldcom). We construct four dummies that attain the values of unity as follows: $(mexican)$ for the period 20/12/1994 to 31/1/1995, $(asian)$ for the period 2/07/1997 to

3/12/1997, $(russian)$ for the period 11/08/1998 to 15/01/1999, and $(scandals)$ (Enron, worldcom) for the period 15/4/2002 to 24/07/2002. Hence we augment the model appearing in (8) with the crises dummies and report estimation results in Table 6[7].

----------***Table 6***----------

Regardless of model specification terrorist activity continues to enter the model with a significantly negative coefficient. In particular, the estimated coefficient is strikingly robust across specifications where the occurrence of terrorist attacks reduces daily returns by an average of 0.042 percent and 0.046 percent based on the three-factor model and the three factor model controlling for global financial crises respectively.

5.2 Terrorism and Stock Returns by level of Psychosocial Impact

In this section we explore the possibility that terrorism's effect on stock returns is related to the level of psychosocial impact. If indeed a sentiment mechanism was responsible for the observed negative relationship between terrorism and returns one would expect the level of psychosocial impact to be crucial. In other words, it is plausible to expect that the effect of terrorist incidents is not uniform across levels of psychosocial impact. In fact we anticipate that the absolute effect monotonically increases with the degree of psychosocial impact. In Table 7 we report the estimation results based on the PP-ARCH(2) specification for the one-factor model and the three-factor model (with and without the crises dummies). Note that the sample corresponds to 1998-2004 since the psychosocial impact variable was not coded for the earlier period.

Irrespectively of which specification is employed the results are qualitatively similar. The null hypothesis that the sum of the psychosocial dummies is zero is comfortably rejected verifying the finding that daily returns are correlated with the overall terrorist activity. In addition the null that all psychosocial dummies' coefficients are insignificant is emphatically rejected suggesting that the effect on returns is not uniform across levels of psychosocial impact. Inspecting the relevant coefficients individually we see that the coefficients of each level of psychosocial impact dummies are negative, although the coefficients of attacks with no and moderate impact are insignificant. As for the remaining two coefficients we find that terrorist incidents with minor psychosocial impact reduce returns on average by approximately 0.07 percent while the reduction in the occurrence of incidents with major psychosocial impact is estimated as being approximately 0.60 indicating that the effect of the latter is about eight times higher of the former. The finding of a differential effect of terrorist incidents, which is increasing in the level of psychosocial impact, is compatible with an underlying sentiment mechanism.

----------***Table** 7*----------

6. Conclusions

The analysis explored whether terrorist activity exerted a significant impact on daily stock market returns for a sample of 22 countries who witnessed a large share of worldwide terrorist activity in the period 1994-2004. The employed empirical specifications were based on flexible versions of the World CAPM allowing for autoregressive conditional heteroscedasticity. The theoretical motivation was provided by the investor sentiment literature where terrorist activity was assumed to impact on investor mood. The results suggest that terrorist activity indeed leads to significantly lower returns on the day of terrorist attack occurrence. In addition, the negative effect of terrorist activity is substantially amplified when terrorist incidents cause higher psychosocial impact. On the one hand this evidence sheds light to the underlying mechanism via which terrorism affects stock markets while on the other hand provides empirical support for the sentiment effect.

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Tables

Table 1. Top 40 Countries in terms of total terrorist incidents (1994-2004) [a,b]

Country	Count of Terrorist Attacks	Cumulative frequency	% of total incidents	Cumulative %
Colombia	1543	1543	9.20	9.20
India	1203	2746	7.17	16.37
Algeria	1188	3934	7.08	23.46
Pakistan	1132	5066	6.75	30.21
Turkey	649	5715	3.87	34.08
Philippines	548	6263	3.26	37.35
UK	538	6801	3.20	40.56
France	527	7328	3.14	43.70
Sri Lanka	517	7845	3.08	46.79
Russia	514	8359	3.06	49.85
Spain	420	8779	2.57	52.36
Israel	402	9181	2.39	54.75
Palestine	345	9526	2.05	56.81
Egypt	326	9852	1.94	58.76
Iraq	291	10143	1.73	60.49
South Africa	279	10422	1.66	62.16
Bangladesh	275	10697	1.64	63.80
Germany	274	10971	1.63	65.43
Mexico	258	11229	1.53	66.97
Lebanon	249	11478	1.48	68.45
Indonesia	236	11714	1.40	69.86
Burundi	230	11944	1.37	71.23
Peru	220	12164	1.31	72.55
Greece	203	12367	1.21	73.76
USA	200	12567	1.19	74.95
Afghanistan	189	12756	1.12	76.08
Guatemala	170	12926	1.01	77.09
Uganda	157	13083	0.93	78.03
Tajikistan	136	13219	0.81	78.84
Haiti	128	13347	0.76	79.60
Thailand	126	13473	0.75	80.35
Somalia	116	13589	0.69	81.05
Nepal	115	13704	0.68	81.73
Cambodia	114	13818	0.67	82.41
Rwanda	110	13928	0.65	83.07
FYROM	103	14031	0.61	83.68
Brazil	102	14133	0.60	84.29
Venezuela	95	14228	0.56	84.86
Angola	89	14317	0.53	85.39
Yemen	85	14406	0.50	85.90

Notes:

a) Terrorism data are based on the Global Terrorism Databases 1 and 2 compiled by the University of Maryland.
b) Terrorist incidents correspond to the sum of domestic and transnational activity.

Table 2. Returns' Descriptive Statistics

Country (Stock Index)	Mean[a]	Maximum	Minimum	Std. Dev.[b]	Skewness	Kurtosis	Jarque-Berra[c]
Brazil (BRAZIL BOVESPA)	0.182	33.39	-15.82	2.65	1.11	17.90	27159.1
Colombia (COLOMBIA IGBC)	0.167	9.30	-6.17	1.15	0.79	13.98	4688.2
Egypt (EGYPT HERMES)	0.045	14.68	-12.01	1.32	0.88	17.04	21791.1
France (CAC40)	0.027	7.25	-7.39	1.40	0.01	5.50	749.2
Germany (DAX)	0.034	7.84	-6.43	1.55	-0.03	5.46	702.2
Greece (ATHEX COMPOSITE)	0.047	7.96	-9.23	1.62	0.10	7.01	1931.1
India (INDIA BSE)	0.034	8.97	-11.13	1.55	-0.03	6.67	1611.1
Indonesia (JAKARTA SE COMPOSITE)	0.031	14.02	-11.95	1.64	0.34	12.10	9966.8
Israel (ISRAEL TA 100)	0.042	10.08	-9.93	1.42	-0.11	8.41	3511.1
Lebanon (LEBANON BLOM)	-0.013	6.62	-5.37	1.09	0.54	7.44	2036.8
Mexico (MEXICO IPC)	0.071	12.92	-13.33	1.68	0.23	9.07	4435.9
Pakistan (KARACHI SE 100)	0.050	13.61	-12.37	1.67	-0.11	10.02	5907.2
Peru (LIMA SE GENERAL)	0.054	7.81	-8.41	1.17	0.09	9.98	5843.9
Philippines (PHILIPPINE SE)	-0.009	17.55	-9.28	1.50	1.08	17.88	27054.4
Russia (RUSSIA RTS)	0.118	16.83	-19.02	2.96	-0.09	8.41	2973.1
Spain (MADRID SE GENERAL)	0.045	5.89	-6.49	1.22	-0.14	5.53	778.8
Sri Lanka (COLOMBO SE ALLSHARE)	0.021	20.06	-12.97	1.19	1.29	46.77	229860.4
Thailand (BANGKOK SET)	-0.016	12.01	-9.54	1.78	0.59	7.56	2659.2
Turkey (ISE NATIONAL 100)	0.212	19.45	-18.10	3.06	0.17	6.64	1598.7
UK (FTSE ALLSHARE)	0.017	5.22	-5.21	0.97	-0.18	6.06	1140.8
USA (NYSE COMPOSITE)	0.038	5.31	-6.56	0.95	-0.16	7.05	1976.6
Venezuela (VENEZUELA SE)	0.135	22.21	-10.24	1.87	1.39	19.12	32012.1
All countries (unweighted)	0.0463	33.39	-19.02	1.77	0.117	14.26	297303

Notes:

a) Mean, Maximum, Minimum, and Std. Dev. are expressed in percentages.
b) Std. Dev. stands for sample standard deviation.
c) Jarque-Berra denotes the normality statistic distributed as a Chi-square with two degrees of freedom.

Table 3. Factor Returns' Descriptive Statistics

Benchmark Portfolios	Mean[a]	Maximum	Minimum	Std. Dev.[b]	Skewness	Kurtosis	Jarque-Berra[c]	CV[d]
World Market Portfolio (MSCI World)	0.0244	4.86	-4.66	0.85	-0.07	6.07	1132.3	34.83
Small (MSCI World)	0.0241	3.62	-3.99	0.70	-0.43	5.83	1012.39	29.04
Large (MSCI World)	0.0227	4.88	-4.81	0.87	-0.09	6.07	1095.36	38.32
SMB (Small – Large)	0.0013	1.74	-2.50	0.44	-0.28	4.87	442.34	-
Value (MSCI World)	0.0272	6.33	-4.67	0.86	0.29	9.81	5594.89	31.61
Growth (MSCI World)	0.0215	5.53	-5.59	0.95	0.03	7.52	2450.00	44.18
HML (Value – Growth)	0.0057	6.33	-5.98	1.20	0.20	6.58	1559.49	-

Notes:

a) Mean, Maximum, Minimum, and Std. Dev. are expressed in percentages.
b) Std. Dev stands for sample standard deviation.
c) Jarque-Berra denotes the normality statistic distributed as a Chi-square with two degrees of freedom.
d) CV stands for the Coefficient of Variation defined as the ratio of sample standard deviation to sample mean.

Table 4. Number of trading days on which terrorist attacks occurred[a,b]

Country	Count of terrorist attacks	Number of trading days on which terrorist attacks occurred
Brazil	102	67
Colombia	1543	624
Egypt	326	187
France	527	238
Germany	274	128
Greece	203	122
India	1203	610
Indonesia	236	127
Israel	402	236
Lebanon	249	155
Mexico	258	148
Pakistan	1132	416
Peru	220	107
Philippines	548	305
Russia	514	331
Spain	420	207
Sri Lanka	517	288
Thailand	126	77
Turkey	649	315
UK	538	309
USA	200	106
Venezuela	95	65
Total	10282	5168

Notes:

a) Attacks carried out either on weekends or days that stock markets were closed (national holidays) are not taken into account.

b) Multiple terrorist incidents on a given trading day are treated as a single event.

Table 5. Terrorism and Stock Returns: One-Factor World Model (1994-2004)

Regressor	Random Effects	PP-ARCH(1) [a]	PP-ARCH(2)
	Point estimate (z-score) [b]		
Mean equation			
$S_{i,t}$	**-0.061**** **(-2.16)**	**-0.057***** **(-2.92)**	**-0.049***** **(-2.90)**
$R_{WMP,t}$	0.413*** (48.21)	0.406*** (90.92)	0.398*** (94.40)
$R_{WMP,t-1}$	0.104*** (11.86)	0.094*** (18.22)	0.094*** (19.28)
$R_{WMP,t-2}$	0.042*** (4.78)	0.039*** (7.55)	0.044*** (8.85)
$R_{WMP,t-3}$	0.063*** (7.11)	0.054*** (9.97)	0.058*** (12.09)
$R_{WMP,t-4}$	0.018** (2.09)	0.025*** (4.84)	0.021*** (4.59)
$R_{WMP,t-5}$	0.012 (1.40)	-0.0001 (-0.03)	0.002 (0.56)
$R_{i,t-1}$	0.079*** (18.40)	0.115*** (79.31)	0.080*** (30.56)
$R_{i,t-2}$	-0.006 (-1.56)	-0.0005 (-0.35)	-0.011*** (-5.68)
$R_{i,t-3}$	-0.015*** (-3.49)	-0.011*** (-6.72)	0.0006 (0.34)
$R_{i,t-4}$	0.014*** (3.26)	0.018*** (10.69)	0.022*** (12.51)
$R_{i,t-5}$	-0.012*** (-2.81)	-0.009*** (-5.99)	0.002 (1.10)
intercept	0.138*** (3.74)	0.109*** (4.06)	0.123*** (5.25)
Year effects[c]	included	included	included
Month effects	included	included	included
Day effects	included	included	included
Conditional Variance Equation			
$\sigma^2_{i,t-1}$	-	0.581*** (107.25)	0.421*** (82.68)
$\sigma^2_{i,t-2}$	-	-	0.365*** (76.61)
intercept	-	1.494*** (231.80)	0.938*** (156.98)
Log Likelihood	-	-101901.30	-98872.40
LR Test[d]: PP-ARCH(2) vs. PP-ARCH(1)		60551***	
Observations		55084	

Notes:

a) PP-ARCH stands for Pooled Panel Autoregressive Conditional Heteroscedasticty.
b) ***, **, * denote significance at the 1, 5 and 10 percent level respectively.
c) Year, Month, Day effects include 10, 11, 4 zero/one dummies identifying each year, month and day.
d) LR stands for Likelihood Ratio.

Table 6. Terrorism and Stock Returns: Sensitivity Analysis based on the PP-ARCH(2) specification[a]

Model	**Three-Factor World Mode**
Regressor	
	Mean equation
$S_{i,t}$	**-0.042****
	(-2.40)
$R_{WMP,t}$	0.444***
	(43.47)
$R_{WMP,t-1}$	0.120***
	(10.02)
$R_{WMP,t-2}$	0.034***
	(2.72)
$R_{WMP,t-3}$	0.060***
	(4.33)
$R_{WMP,t-4}$	-0.006
	(-0.49)
$R_{WMP,t-5}$	0.022**
	(2.25)
$R_{SMB,t}$	-0.040***
	(-3.73)
$R_{SMB,t-1}$	0.123***
	(10.62)
$R_{SMB,t-2}$	0.066***
	(5.37)
$R_{SMB,t-3}$	0.032***
	(2.72)
$R_{SMB,t-4}$	-0.003
	(-0.27)
$R_{SMB,t-5}$	0.008*
	(0.71)
$R_{HML,t}$	0.006
	(1.31)
$R_{HML,t-1}$	0.001
	(0.20)
$R_{HML,t-2}$	-0.006
	(-0.80)
$R_{HML,t-3}$	0.006
	(0.77)
$R_{HML,t-4}$	-0.001
	(-0.15)
$R_{HML,t-5}$	0.025***
	(3.15)
$R_{i,t-1}$	0.074***
	(28.40)
$R_{i,t-2}$	-0.013***
	(-6.19)
$R_{i,t-3}$	-0.001
	(-0.84)
$R_{i,t-4}$	0.022***
	(12.52)
$R_{i,t-5}$	0.002
	(1.19)
intercept	0.111***

	(4.75)
Year effects[c]	included
Month effects	included
Day effects	included
Crises Dummies [d]	-
	Conditional Variance Eq
$\sigma_{i,t-1}^{2}$	0.424***
	(81.98)
$\sigma_{i,t-2}^{2}$	0.361***
	(73.34)
intercept	0.930***
	(150.86)
Log Likelihood	-95298.98
Observations	53302

Notes:

a) PP-ARCH stands for Pooled Panel Autoregressive Conditional Heteroscedasticity.
b) ***, **, * denote significance at the 1, 5 and 10 percent level respectively.
c) Year, Month, Day effects include 10, 11, 4 zero/one dummies identifying each year, month and day.
d) Crises dummies correspond to *mexican*, *asian*, *russian*, and *scandals* which are dummies attaining the value of unity for the periods (2(

Table 7. Terrorism and Stock Returns by level of Psychosocial Impact (1998-2004)

Model	**One-Factor World Model**	**Three-Factor World Model**	**Three-Factor World Model controlling for financial crises**
Regressor	**Point estimate (z-score)** [a]		
	Mean equation		
$\left(NON_{i,t}\right)$	**-0.018**	**-0.017**	**-0.017**
	(-0.20)	**(-0.19)**	**(-0.19)**
$\left(MIN_{i,t}\right)$	**-0.075****	**-0.066****	**-0.070****
	(-2.48)	**(-2.16)**	**(-2.32)**
$\left(MOD_{i,t}\right)$	**-0.055**	**-0.060**	**-0.061**
	(-0.39)	**(-0.43)**	**(-0.44)**
$\left(MAJ_{i,t}\right)$	**-0.630***	**-0.619***	**-0.623***
	(-1.83)	**(-1.78)**	**(-1.79)**
$R_{WMP,t}$	0.396***	0.410***	0.409***
	(74.72)	(18.31)	(18.31)
$R_{WMP,t-1}$	0.103***	0.215***	0.219***
	(17.01)	(5.34)	(5.43)
$R_{WMP,t-2}$	0.044***	-0.079	-0.077
	(7.17)	(-1.64)	(-1.60)
$R_{WMP,t-3}$	0.059***	0.185***	0.187***
	(10.08)	(3.92)	(3.94)
$R_{WMP,t-4}$	0.018***	-0.094**	-0.094**
	(3.20)	(-2.42)	(-2.40)
$R_{WMP,t-5}$	0.003	0.043**	0.045**
	(0.64)	(2.22)	(2.29)
$R_{SMB,t}$	-	-0.013	-0.012
		(-0.96)	(-0.87)
$R_{SMB,t-1}$	-	0.134***	0.136***
		(9.29)	(9.41)
$R_{SMB,t-2}$	-	0.063***	0.066***
		(4.11)	(4.25)
$R_{SMB,t-3}$	-	0.053***	0.053***
		(3.62)	(3.66)
$R_{SMB,t-4}$	-	-0.016	-0.016
		(-1.05)	(-1.08)
$R_{SMB,t-5}$	-	0.021	0.021
		(1.50)	(1.52)
$R_{HML,t}$	-	0.011	0.012*
		(1.59)	(1.67)
$R_{HML,t-1}$	-	0.042**	0.044**
		(2.17)	(2.31)
$R_{HML,t-2}$	-	-0.058**	-0.057**
		(-2.33)	(-2.27)
$R_{HML,t-3}$	-	0.074***	0.076***
		(2.82)	(2.86)
$R_{HML,t-4}$	-	-0.065***	-0.064***
		(-2.71)	(-2.67)
$R_{HML,t-5}$	-	0.045***	0.046***
		(2.60)	(2.63)
$R_{i,t-1}$	0.041***	0.039***	0.037***
	(14.55)	(13.37)	(12.96)
$R_{i,t-2}$	-0.015***	-0.016***	-0.017***
	(-4.91)	(-5.46)	(-5.78)

$R_{i,t-3}$	-0.002	-0.001	-0.001
	(-0.99)	(-0.74)	(-0.58)
$R_{i,t-4}$	0.029***	0.029***	0.030***
	(13.18)	(12.97)	(13.31)
$R_{i,t-5}$	0.006**	0.006***	0.006***
	(2.55)	(2.54)	(2.69)
intercept	0.157***	0.140***	0.137***
	(5.29)	(4.71)	(4.60)
Year effects[b]	included	included	included
Month effects	included	included	included
Day effects	included	included	included
Crises Dummies[c]	-	-	included
Conditional Variance Equation			
$\sigma^2_{i,t-1}$	0.388***	0.390***	0.391***
	(64.08)	(64.33)	(64.25)
$\sigma^2_{i,t-2}$	0.350***	0.348***	0.350***
	(59.19)	(57.25)	(57.34)
intercept	1.098***	1.096***	1.092***
	(124.52)	(122.32)	(121.62)
Sum of psychosocial coefficients is zero[d]	4.10**	3.87**	3.97**
All psychosocial coefficients are zero[e]	9.60**	7.98*	8.74**
Log Likelihood	-66852.21	-66806.41	-66801.07
Observations	36302	36302	36302

Notes:

a) ***, **, * denote significance at the 1, 5 and 10 percent level respectively.

b) Year, Month, Day effects include 10, 11, 4 zero/one dummies identifying each year, month and day.

c) Crises dummies correspond to *Russian* and *scandals* which are dummies attaining the value of unity for the periods (11/08/1998 to 15/01/1999), and (15/4/2002 to 24/07/2002) respectively.

d) The statistic is distributed as a Chi-square with 1 degree of freedom.

e) The statistic is distributed as a Ch-square with 4 degrees of freedom.

Figures

Figure 1 Terrorist Attacks with Moderate and Major Psychosocial Impact by Year

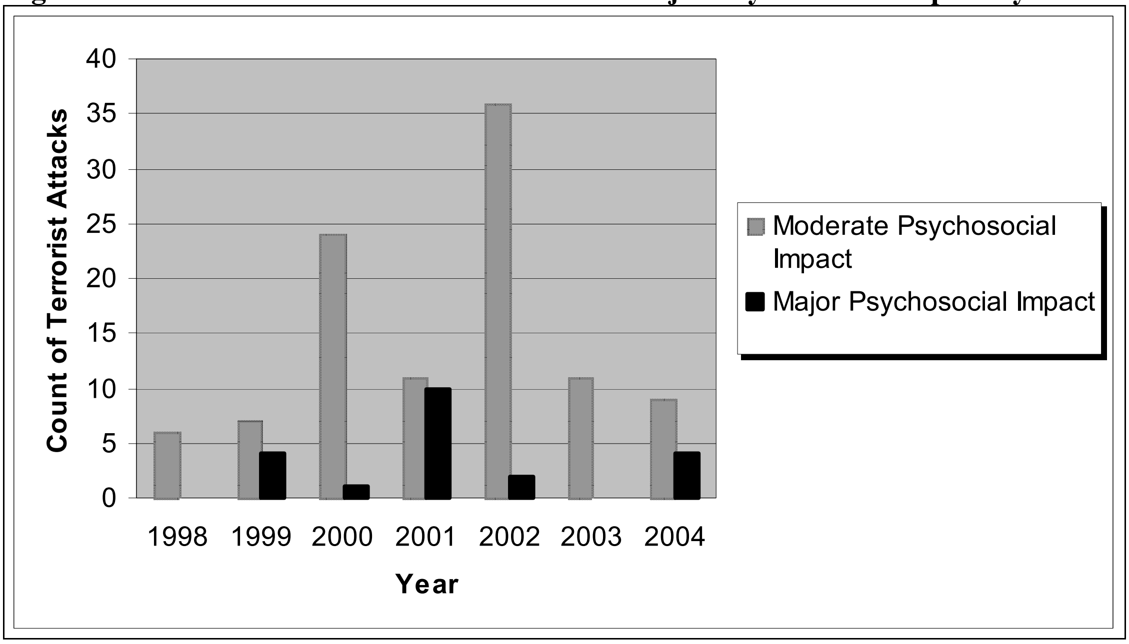
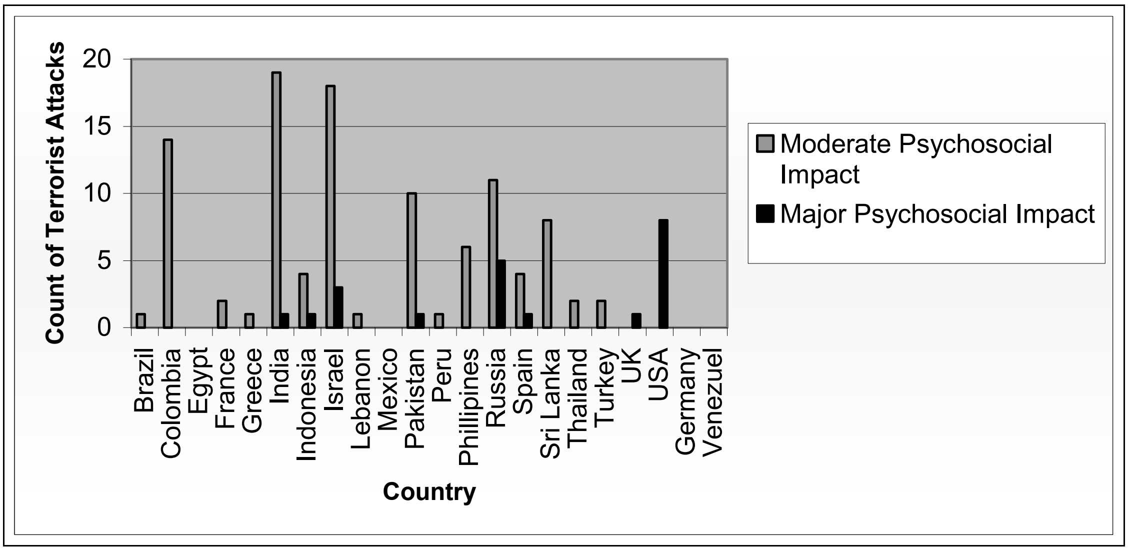


Figure 2 Terrorist Attacks with Moderate and Major Psychosocial Impact by Country



Endnotes

[1] Also known as macroterrorism describing terrorism incidents causing more than $1 billion of loss, or 500 deaths (Woo, 2003).
[2] The conditional international capital asset pricing model would hold if capital markets were fully integrated and therefore the risk-adjusted expected return on all assets should be the identical across countries.
[3] "The employed definition of terrorism is the threatened or actual use of illegal force and violence to attain a political, economic, religious, or social goal through fear, coercion, or intimidation.", source: Global Terrorism Database 1.1, 1970-1997 user guide.
[4] Data for 1993 are not available.
[5] "In order to be considered as a "terrorist incident" the event had to have been committed by non-state actors, had to have been violent, and intentional. In addition the act must have met two of the following three criteria: (1) The act must have been aimed at attaining a political, economic, religious, or social goal. In terms of economic goals, the exclusive pursuit of profit did not satisfy this criterion. (2) There must have been evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims. (3) The action must have been outside the context of legitimate warfare activities, *i.e.* the act must have been outside the parameters permitted by international humanitarian law (particularly the admonition against deliberately targeting civilians or noncombatants).", source Global Terrorism Database II, 1998-204 user guide.
[6] During the period 1994-2004 terrorist incidents were recorded in a total of 180 countries.
[7] The table reports only results from the PP-ARCH(2) model for space conservation reasons. The full set of results for Random Effects and PP-ARCH(1) are available upon request by the authors.